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Spatiotemporal Data Prediction Model Based on a Multi-Layer Attention Mechanism

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ABSTRACT

Spatiotemporal data prediction is of great significance in the fields of smart cities and smart manufacturing. Current spatiotemporal data prediction models heavily rely on traditional spatial views or single temporal granularity, which suffer from missing knowledge, including dynamic spatial correlations, periodicity, and mutability. This paper addresses these challenges by proposing a multi-layer attention-based predictive model. The key idea of this paper is to use a multi-layer attention mechanism to model the dynamic spatial correlation of different features. Then, multi-granularity historical features are fused to predict future spatiotemporal data. Experiments on real-world data show that the proposed model outperforms six state-of-the-art benchmark methods.

KEYWORDS

Attention Mechanism, Data Mining, Dynamic Spatial Relationships, Encoder-Decoder, LSTM, Multiple Temporal Relationships, Smart Cities, Spatiotemporal Data Prediction

INTRODUCTION

With the development of the mobile Internet, the requirements for data processing efficiency and mining depth are increasing rapidly (Zheng et al., 2014). As an important research field of spatiotemporal data processing, it is of great significance in accelerating the process of smart city construction (Bai et al., 2019) and manufacturing (Ge et al., 2011) in China and has been widely applied in a number of scenarios, such as air quality prediction (Wang et al., 2021; Pan et al., 2019), traffic flow prediction (Pan et al., 2019; Gong et al., 2019; Pan et al., 2022), medical risk prediction (Ye et al., 2020) and industrial production prediction (Cho, S., et al., 1997).

Current spatiotemporal data prediction models make some achievements. ARIMA (George & Gwilym, 1976) enables the extraction of the linear relationships between data while ignoring the complex nonlinear relationships, leading to low accuracy. ANN (Hopfield, 1982) represents complex nonlinear functions with an integrated structure of linear threshold units and partly discovers medium- and long-term patterns of spatiotemporal data (Martin et al., 2017). However, the results

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are sensitive to the initial random weights and thresholds, which would be quite challenging in the case of real industrial production owing to the high demand for reliability. Support vector machines (SVMs) (Bernhard et al., 1992) are designed to map the input vector to a high-dimensional space and analyze the nonlinear characteristics of the sample using a linear algorithm to improve the accuracy (Sapankevych, N., & Sankar, R., 2009). Unfortunately, it is difficult to build a common prediction model because of the prior domain knowledge and the sensitivity of parameters and kernel functions. Random forests (Emmanouil, A., et al., 2019) train multiple decision trees for joint prediction. These methods are effective in extracting complex nonlinear relationships between high-dimensional data, and they are prone to overfitting when data noise exists. Convolutional neural networks (Yann, L., et al., 1998) model the spatial correlations of data through operations such as convolution and pooling, but they are highly dynamic and easily affected by multiple features (Liu et al., 2016; Shao et al., 2022; Zhong et al., 2022). Recurrent neural networks (Tomáš et al., 2011; Yang et al., 2022) can be used to extract historical patterns in spatiotemporal data by updating the model parameters by a backpropagation algorithm. Most existing studies use recurrent neural networks to capture a single temporal correlation (Yao et al., 2019; Wang, Y., & Liu, 2022; Hou et al., 2021) without considering the compounding effects of periodicity and abrupt variability on the data, making insufficient use of historical data.

Data in real scenarios such as smart cities and smart manufacturing have the following characteristics. In terms of sampling, the data quality is poor and locally sparse owing to the real-world environment and limited cost. For the spatial dimension, there exist correlations between both features and spatiotemporal objects. For the temporal dimension, the spatiotemporal data have both periodicity and mutability, while historical data of different granularities have different effects on the prediction results. These characteristics make it difficult for existing models to accurately model the evolution process of complex spatiotemporal data.

To solve the these problems, the authors propose a multilayer attention prediction model (spatiotemporal data prediction based on multilayer attention, STDPMA), which analyzes the interaction between different features and captures the dynamic spatial correlations of data. They then incorporate the cyclical and sudden change characteristics to fuse the historical features of multiple granularities.

This paper's contributions are summarized as follows:

- To solve the problem of local sparsity of data, the authors leveraged spatial interpolation based on the spatial correlations between regions. The experimental results show that this spatial interpolation method will not destroy the temporal relationship of the original data. It can be applied to similar applications.
- To model the dynamic spatial correlations, features were divided according to their nature and extract dynamic spatial correlations between spatiotemporal objects. Historical features were then extracted by hour without introducing noise.
- A multigranularity encoder-decoder-based fusion network was designed to effectively fuse the patterns of the three granularities according to the periodicity and abruptness. Specifically, a multilayer attention mechanism was introduced to measure the influence of three granularity embeddings from the encoder module and leverage the decoder module to predict future spatiotemporal data.

RELATED WORK

Spatiotemporal data are used in the analysis when data are collected across both space and time. Prediction models must capture both spatial and temporal dependencies.

To model spatial correlations, more recent studies propose to capture high-order spatial correlations (from both static and dynamic views) using multiple convolutional neural networks

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